

Fault Diagnosis Approach for WSN using Normal Bias Technique

Poornima G¹ K Suresh Babu² K B Raja² K R Venugopal² L M Patnaik³

¹Dept of Electronics and Communication Engineering, BMSCE, Bangalore, India

²Dept of Computer Science and Engineering, UVCE, Bangalore, India

³Honorary Professor, Indian Institute of Science, Bangalore, India

gpoornima.ece@bmsce.ac.in

Abstract: In wireless sensor and actor networks (WSAN), the sensor nodes have a limitation on lifetime as they are equipped with non-chargeable batteries. The failure probability of the sensor node is influenced by factors like electrical dynamism, hardware disasters, communication inaccuracy and undesired environment situations, etc. Thus, fault tolerant is a very important and critical factor in such networks. Fault tolerance also ensures that a system is available for use without any interruption in the presence of faults. In this paper an improved fault tolerance scheme is proposed to find the probability of correctly identifying a faulty node for three different types of faults based on normal bias. The nodes fault status is declared based on its confidence score that depends on the threshold value. The aim is to find the Correct Recognition Rate (CRR) and the False Fear Rate (FFR) with respect to the different error probability (p_e) introduced. The techniques, neighboring nodes, fault calculations, range and CRR for existing algorithm and proposed algorithm is also presented.

Keywords: Wireless Sensor and Actor Networks, Fault Tolerance, Normal Bias, Failure Probability, Correct Recognition Rate, False Fear Rate.

I. INTRODUCTION

Wireless sensor networks (WSN) consist of spatially distributed sensor nodes that can communicate with each other, the desired physical quantity such as temperature, sound, tremor, force, motion or noxious waste are measured by the sensors. The Sensors are devices with low cost and powered having limited energy for computation and wireless communication capabilities. WSNs are advantageous because the end devices are compact and rugged, requiring little power to operate and can be deployed for reliable, long term, remote operations. WSNs enabled numerous advanced monitoring and control application in environmental, biomedical, military and other applications. Some of the most common WSN applications include environmental analysis, physical health checking and device watching. The Communication in sensor networks is unpredictable and failure-prone due to which the network is said to be vulnerable. When the network is supporting more and more applications and services, the impact of failure of a network will be more obvious, so improving networks fault tolerance is practical and important.

Data delivery in sensor networks is inherently faulty and unpredictable. Failures in wireless sensor networks can occur

for various reasons. First, sensor nodes are brittle, and they may fail due to exhaustion of batteries or damage by an external event. In addition, nodes may seize and communicate wrong readings because of environmental influence on their sensing components. Secondly, as in wireless ad hoc networks, the links are prone to failure, triggering network partitions and initiate active changes in network topology. The external object or environmental conditions may fail the links permanently or block temporarily. Packets may be ruined due to the flawed nature of communication. Third, congestion triggers packet loss, it is mainly because a number of nodes coinciding transitions from a power saving state to an active transmission state in response to an event-of-interest [1].

Conventional networks are not concerned with energy consumption due to the fact that wired networks are continuously powered and wireless ad hoc devices are recharged repeatedly. The protocols for these networks are aimed at achieving point-to-point reliability, whereas wireless sensor networks are concerned with reliable event detection. In sensor networks, node failure occur more frequently than wired, where servers, routers and client machines are assumed to operate normally, significant overhead is desired. The protocols in fixed network bank on handy MAC layer protocols that avoid packet collisions, hidden terminal problem and channel errors by using physical carrier sense (RTS/CTS) and virtual carrier sense (monitoring the channel); in wireless sensor networks. The protocols at the MAC layer have to meet additional challenges, such as synchronizing a node's sleeping and wake times, and it can only diminish the packet collision problem, but cannot give an absolutely solution. These remarks directs that new fault tolerant protocols are necessary for sensor applications to operate successfully and that these protocols should ensure reliable data delivery while minimizing energy consumption.

In customary distributed systems the nomenclature of different fault tolerant techniques used is [2]. Fault prevention: this is to avoid or prevent faults. 2. Fault detection: this is to use different metrics to collect symptoms of possible faults. 3. Fault isolation: this is to correlate different types of fault indications (Alarms) received and suggest different fault hypotheses. 4. Fault identification: this is to test each of the proposed guesses in order to exactly localize and recognize faults. 5. Fault recovery: this is to treat faults, i.e., reverse their adverse effects. There are techniques that address a combination of all these aspects. These techniques work at

diverse layers of the network protocol stack. Major fault avoidance procedures operate in the network layer, accumulation redundancy in forwarding paths; a majority of fault detection and recovery methods run at the transport layer; and a few fault recovery practices execute at the application layer, masking faults for the duration of off-line data processing. In WSNs the communication between sensors is less reliable, i.e. messages may be lost due to noise. Fault tolerance also ensures that a system is available for use without any interruption in the presence of faults; thus fault tolerance increases the reliability, availability and consequently dependability of the system.

Contribution: - In this paper FTNB is proposed. The paper addresses three different classes of faults that are the preset, balanced and unsymmetrical faults. The faulty nodes under these categories are identified effectively based on the normal bias.

Organization: - The paper is organized as follows. In section 1 introduction to fault management for wireless sensor networks is discussed. The literatures of various exiting schemes to handle fault tolerance are elaborated in section 2. In section 3 the proposed method for fault tolerance based on FTNB is presented. In section 4 the problem with algorithm and in section 5 results are discussed. The finishing remarks are specified in Section 6.

II. LITERATURE SURVEY

The problem of positioning or fixing a sensor network to guarantee a definite level of multipath connectivity between all nodes is discussed in [3]. To handle node catastrophes, a greedy and distributed algorithm that produces high-quality placements of additional sensors based on absolute minimum is considered. The optimal redundancy level that could satisfy QOS requirements while increasing the lifetime of the WSN is discussed by Ing-Ray Chen et al., [4]. Lifan Yuan et al., [5] used Neural Network for classifying faulty nodes; they concentrate on pre-processing functions of neural networks and used entropy and kurtosis as the two feature parameters to identify the faulty nodes. Hong Qiao et al., [6] proposed a novel method called a reference model approach to analyze the stability of dynamic network. Depending on whether the neural states or local field states are taken as basic variables, a dynamical neural network is divided into static neural network model and local field neural network model. In [7] fault tolerance using modified hausdorff distance method that determines the correct data range to be detected by the sensor nodes is discussed, the actor node makes use of the data range to identify a faulty node.

In [8] a group of tasks are assigned to the node pairs and the outcomes are compared by neighboring nodes. They use generalized comparison model (GCM) with neural network. The gatherings of all agreements and disagreements are used to identify the set of permanently faulty nodes. Kuo-Feng et al., [9] has proposed an approach where the data inconsistency failure is dealt by forwarding the data through multiple paths. To identify the suspicious node in the faulty

path, a sink node sends diffusion data packets back to the source node through both correct and faulty paths. Staddon et al., [10] proposed two approaches of resuming the network routing paths from the silent nodes (i.e., failed nodes) that are detected in each network routing update epoch. The particle swarm optimization algorithm to deal with fault coverage and also ensure network connectivity is discussed by Peng Li et al., [11]., According to this algorithm the nodes only in the fault region Participate in self-organized movement hence saving energy, and increase network lifetime. Duk-Jin Kim and B. Prabhakaran., [12] has proposed fault node detection algorithms for BSNs that work with different types of features extracted from a sensor node data based on node history and without node history. Stefano et al., [13] considered a solution to recover data loss after a node failure by duplicating and distributing redundant information of sensed data among other nodes in advance. Koushanfar et al., [14] suggested a heterogeneous back-up scheme for tolerating and healing the hardware malfunctions of a sensor node. The key idea is to adapt application algorithms and/or operating systems to match the available hardware and the requirements of the application. The online based distributed fault detection algorithm [15] for multiple sensors averages the history of samples reducing the detection delay for a fixed false alarm. Charu Virmani and Khushboo Garg [16] has discussed various existing adaptive fault tolerant algorithms and compared each of their effectiveness. In [17] dual-weighted trust evaluation scheme to detect malicious and malfunctioning node for hierarchical sensor network is proposed. Trust values of sensor nodes are used as weights at the forwarding node to reflect the event.

A. Background

The fault tolerance using quartile method where correct sensor nodes are detected based on data discreteness has been proposed by Chiu-Ching Tuan et al., [18]. This method is applied for small network with automated structure having variable range and the correct recognition rate achieved is 93.9%. Chen J.R et al., [19] and Peng Jiang [20] have discussed distributed fault detection and improved distributed fault detection scheme for detecting faulty nodes. This method applies to semi-automated architecture with fixed range and small network resulting in a recognition rate of 94%.

III. PROPOSED METHODOLOGY

In this section fault tolerance in wireless sensor and actor networks is built based on Normal Bias Method (FTNB) as shown in the Figure 1.

A. Network Initialization

Nine Hundred sensor nodes are randomly deployed in a 30*30 m area. All the nodes in the network have the same transmission range of 3m. The Nodes with faulty sensors and permanent communication faults (including lack of power) are to be identified, and to be removed or isolated from the network. Sensor nodes which generate incorrect sensing data or fail in communication intermittently are treated as

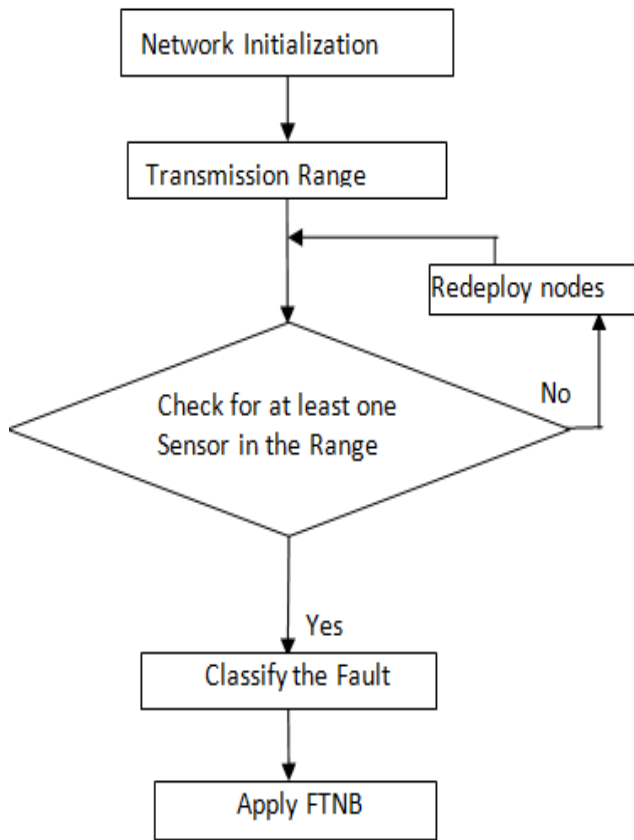


Fig.1.Flow Chart of FTNB

operational nodes, and thus are diagnosed as intermittently faulty, i.e nodes that misbehave occasionally and can be considered for communication. The node deployment should be such that at least one or more nodes are in the communication range of the source node as shown in figure 2; else the network should be redeployed till this condition is achieved.

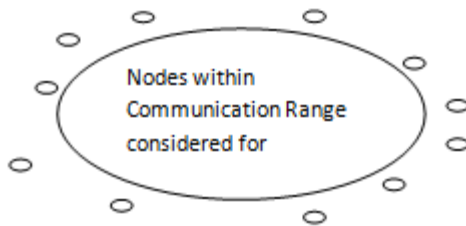


Fig. 2: Nodes within Range are listed for Communication

The placements of nodes are dense and due to this the spatial correlations are satisfied. For each fault-free sensor node its neighbouring fault-free sensor nodes have similar sensing values. Let v_i and v_j be neighbours of each other and x_i denote the sensed data at node v_i . Then the condition to be satisfied by v_i and v_j is $|x_i - x_j| \leq \Delta$ where ' Δ ' may vary depending on the applications. For example if the monitored parameter is temperature then two neighbour sensors should exhibit similar value where the difference i.e ' Δ ' will be very small approximately 0.3.

B. Classify Faults

Fault may occur at different levels of WSN, such as

physical layer, hardware, system software, and middleware. As sensors are most prone to malfunction, the focus is on the fault-free sensors, i.e nodes are able to communicate and process when their sensors are faulty. Taking account of sensor measurements, the following sensor fault models are considered: (i) Preset fault, a fault sensor constantly report a preset value. (ii) Balance fault, the measured data of a faulty sensor is manifested as a calibration offset to the right value. (iii) Unsystematic fault, the measured data of a faulty sensor is affected by a zero-mean noise with high variance.

C. Fault Tolerance by Normal Bias Method

Any sensors v_i is detecting or sensing valve x_i . The node v_i has a set of 'N' neighbors that also sense valve given by x_j ($j=1, 2, 3, \dots, N$) and their corresponding bias are λ_j ($j=1, 2, 3, \dots, N$). The normal bias can now be calculated using the following equation (1).

$$X_i = \frac{\sum_{j=1}^N (\lambda_j x_j)}{\sum_{j=1}^N (\lambda_j)} \quad (1)$$

A reward function shown in equation (2) is defined based on the sensed and normalized value. The reward function then decides the confidence score. Initially the confidence score is set to a maximum value then it is decremented in each round. If the confidence score is reduced to zero the node is declared faulty.

$$f(x_i, X_i) = \begin{cases} 0, & \text{if } |x_i - X_i| \leq \Delta \\ 1, & \dots \text{else where} \end{cases} \quad (2)$$

In order to measure the correctness of the detected faults two parameter alpha and beta are defined. Where alpha represents the faulty nodes and beta represents the fault free nodes detected as faulty. Using these parameters the performance of the algorithm in terms of correct recognition rate and the false fear rate are measured.

IV. ALGORITHM

Problem Definition: The FTNB is used to categorize the type of fault and also detect the faulty node. The actor node based on the received value performs appropriate action by either discarding or accepting data from an intended node. The objective is to detect nodes that read faulty valves by collecting the neighbour node valves and also identified the fault class of the node. The fault reading nodes are isolated from transmitting the faulty valves to the actor temporarily or permanently based on the type of fault class. The implementation steps of FTNB algorithm is discussed in the Table I.

V. RESULTS AND DISCUSSION

The performance of the proposed method is evaluated by MATLAB version 7.7b R2008. For simulation it is assumed that faults are independent of each other. Nine Hundred sensor nodes are deployed randomly in a network area of 30*30m. The nodes only within the transmission range of "3 participate in communication. The neighbour nodes list for a source is generated based on the normal bias and the

TABLE I: PROPOSED FTNB ALGORITHM

Data:	A list of node array within range, num2str (i) {I varying from 1: N}
Result:	An estimate of correct recognition rate and false fear rate.
Begin: Count=0 {For i=1:1: ρ (time instance for each node) For j=1: N x _i = Reading from Sensor ls =Randomly generated Neighbour list Random list of faulty nodes=list For K=1: length (ls) Set initial confidence score=1 Find X _i If f (x _i , X _i)>threshold Decrement confidence score If f (x _i , X _i) =threshold Return (faulted node)} For i=1: size (faulted node, 1) kk=result of the comparison between (faulted node, list) If is empty(kk) Returns (0) Faulty free detected faulty = Faulty free detected faulty +1 Else Returns (1) Faulty node =Faulty node+1 End CRR= Faulty node / (size (list, 1)) FFR= Fault free detected as faulty / (node-size(list,1))	

confidence score set. The performance parameters such as Correct Recognition Rate (CRR) and False Fear Rate (FFR) are used to evaluate the algorithm.

(i)Correct Recognition Rate: It is defined as the ratio of the number of faulty sensor nodes detected to the total number of faulty nodes as shown in Equation 3.

$$CRR = \frac{\text{No. of fault Sensor nodes detected}(\alpha)}{\text{No. of sensor nodes actually faulty}(N \cdot p_e)} \quad (3)$$

Where N is the number of nodes deployed and p_e is the error probability. Typically the value of CRR should be 1 but, as probability increases CRR drops.

(ii)False Fear Rate: It is defined as the of the number of fault-free sensor nodes diagnosed as faulty to the total number of fault-free nodes as shown in Equation 4.

$$FFR = \frac{\text{No. of fault free Sensors detected faulty}(\beta)}{\text{No. of actual fault free Sensor nodes}(N \cdot (1 - p_e))} \quad (4)$$

Ideally the value of FFR should be 0 but, as error probability increases FFR increases. The error probability to the network is varied from 0.05 to 0.3. -If the error is increased beyond 0.3 then the CRR decreases and FFR increases that will drop the performance of the algorithm below 90%.

Table II shows the CRR and FFR for three categories of faults for a failure ratio of 0.2. The performance of the algorithm depends on the number of sensors nodes deployed in the event area, the failure ratio introduced the defined threshold and the type of fault as the each fault is independent of the

TABLE II: COMPARISON OF DIFFERENT TYPES OF FAULTS

Fault Category	Preset Fault	Balanced Fault	Unsystematic Fault
No of Nodes in Transmission Range and Source ID	388	507	377
Neighbor List ID	52,158, 240,262, 378,545, 885	116,308, 361,425, 491, 782	80,135,184, 248,257,276,487, 610,672
Faulty Nodes	178	173	162
Fault Free detected Faulty	2	7	18
FFR	0.052	0.060	0.058
CRR	0.9778	0.9887	0.9722

other. For each fault condition and a failure probability the node reads for 20 time instances. The source node and its neighbour list is short listed. The percentages of nodes that are fault free and faulty are calculated depending on number of nodes deployed and node failure introduced to calculate FFR and CRR.

Figures 3, 4 and 5 shows the results of CRR and FFR (figure of merit) for different error probabilities valves introduced. It is observed from the graph that network can sustain faults up to 0.2 error probability and show Correct Recognition Rate of above 95% and maintaining the False Fear Rate below 0.05 for the preset and balanced fault while below 0.1 for unsystematic fault due its random nature. The different failure probability levels help in handling different type of faults like preset, balanced and unsystematic faults. To reduce the size of the exchange message a neighbor list is prepared, by this node location and every sensor reading message size is avoided ie., only those nodes in the neighbor list will be eligible for communications is reduced that in turn reduces the energy spent by the node. Here the nodes communicate only with nodes in its fault tolerance range. The message exchange is between the node and neighbor nodes and this does not require routing protocol there by contributing to network lifetime by minimal communication.

A. Preset fault

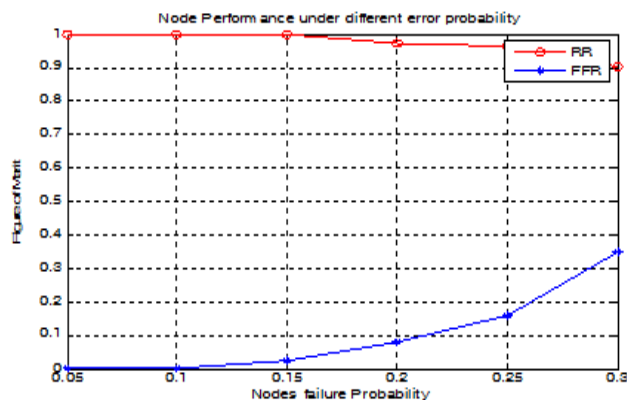


Fig.3: Variation of CRR and FFR (Preset Fault) with Error Probability

B. Balance fault

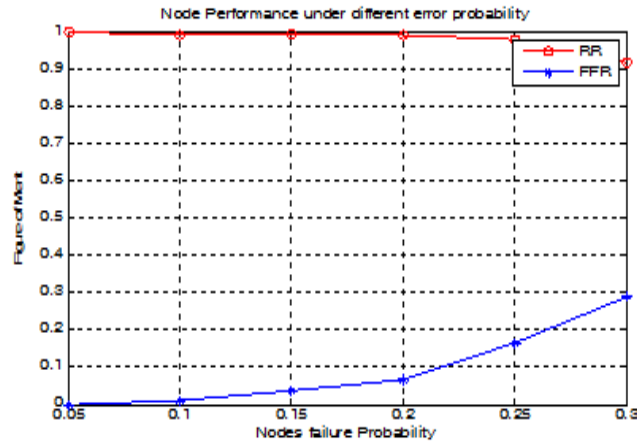


Fig.4: Variation of CRR and FFR (Balance fault) with Error Probability

C. Unsystematic fault

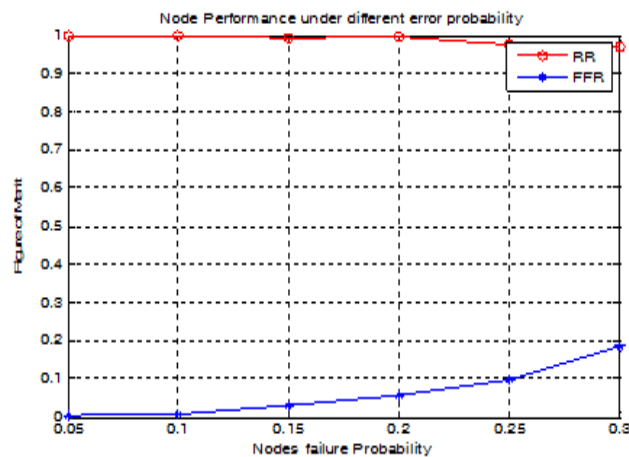


Fig.5: Variation of CRR and FFR (Unsystematic fault) with Error Probability

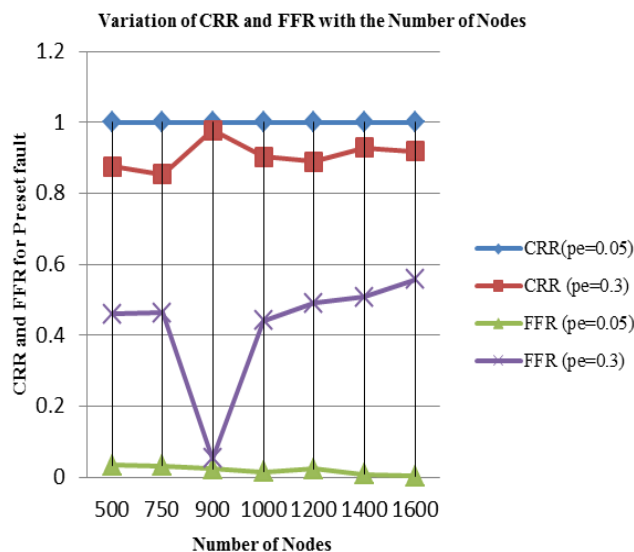


Fig.6: Variation of CRR and FFR (Preset Fault) with the Number of Nodes

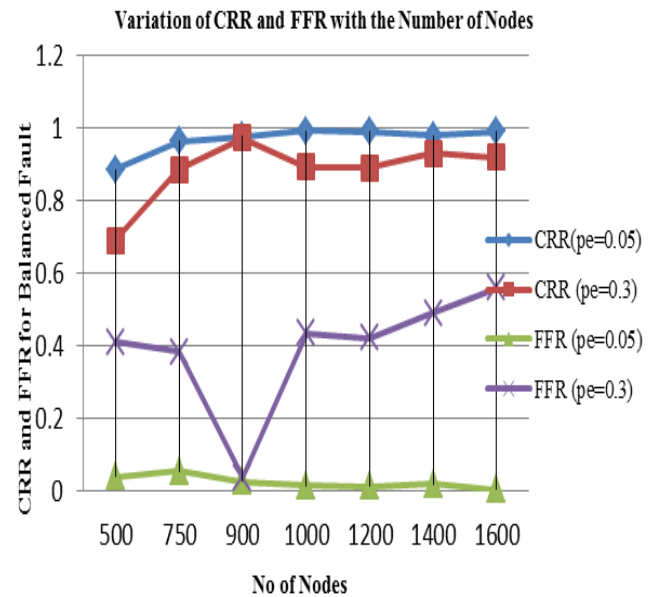


Fig.7: Variation of CRR and FFR (Balanced Fault) with the Number of Nodes

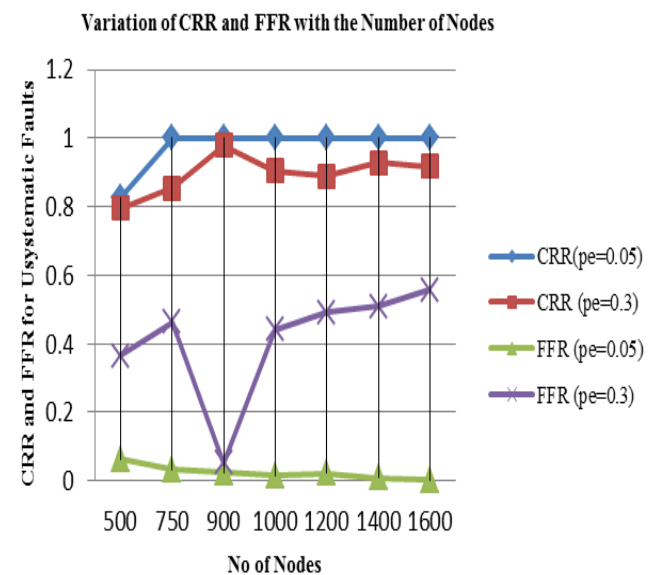


Fig 8: Variation of CRR and FFR (Unsystematic Fault) with the Number of Nodes

Figure 6, 7 and 8 shows the variation of CRR and FFR for varying number of node deployment keeping the communication range constant at “3 for all the three types of faults. It is observed that the algorithm performs better for lower error probability. The FFR increases as error probability increases as more number of sensors misbehaves.

Figure 9, 10, and 11 show the variation of CRR and FFR keeping the number of nodes constant i.e., for node deployment value of 900 nodes and varying the range of communication for the all three category of faults. It is observed that the results are best obtained from the algorithm for a node deployment of 900 when the range is “3 and the error is 0.05. The performance of the algorithm drops with error of 0.3, as the number of fault free sensors detected as faulty increases.

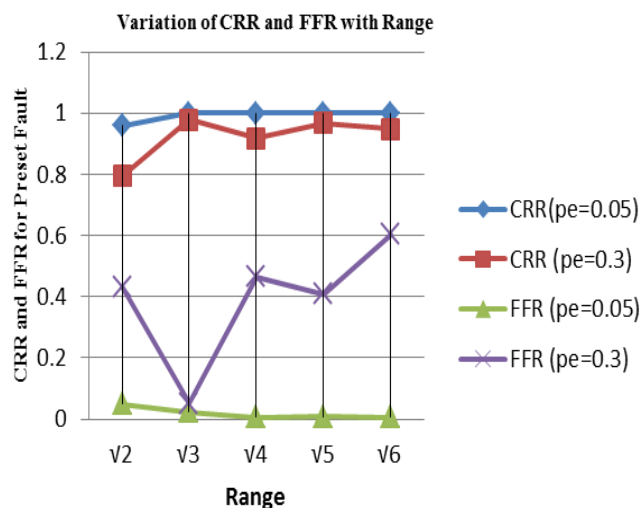


Fig.9 : Variation of CRR and FFR (Preset Fault) with Range

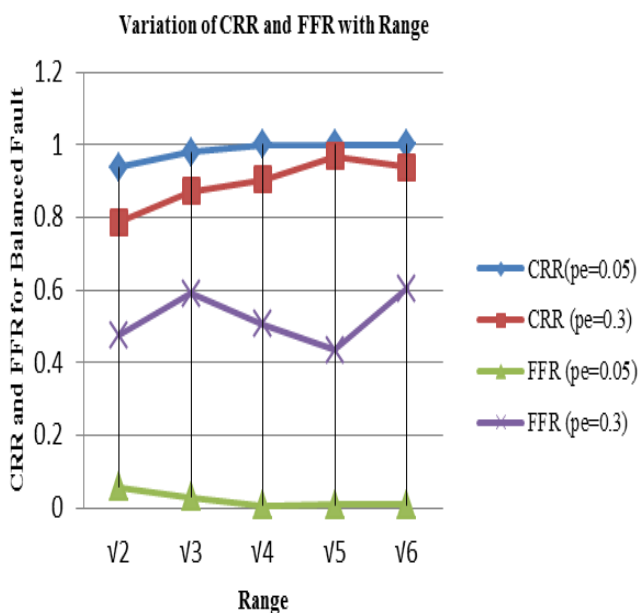


Fig.10: Variation of CRR and FFR (Balance fault) with Range

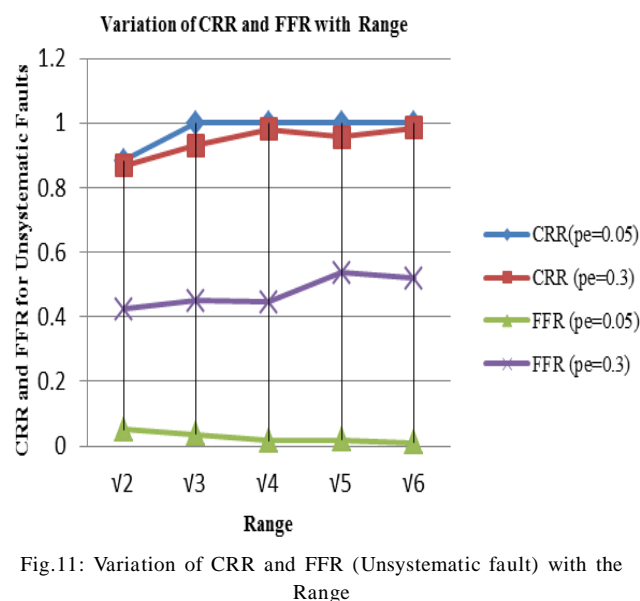


Fig.11: Variation of CRR and FFR (Unsystematic fault) with the Range

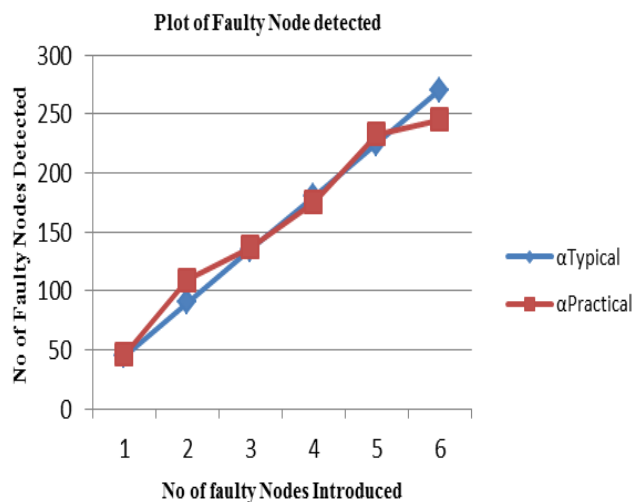


Fig.12: Plot of No of Actual Faulty Nodes Vs No faulty Nodes detected

Figure 12 shows the number of faulty nodes introduced to the number of faulty nodes detected. It is observed the number of faulty nodes detected is almost equal to the number of faulty nodes introduced. Hence our algorithm is better.

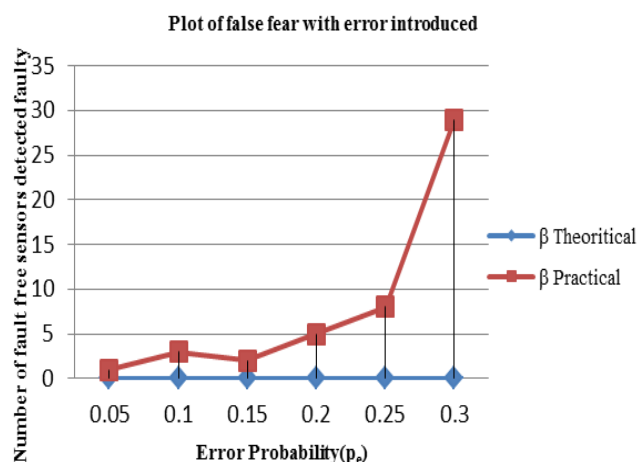


Fig.13: Plot of No of Fault Free Nodes detected faulty

Figure 13 shows the plot of number of fault free sensors detected as faulty. It is observed that the number of fault free sensors detected as faulty is very low up to error probability of 0.15 and the number of fault free sensors detected as faulty increases very much as the error probability is increased from 0.15 to 0.3.

The techniques, fault calculations, neighbouring nodes, range and CRR for existing algorithm and proposed algorithm are tabulated in Table 3. The Chiu Ching Tuan et al., [18] used AFTM technique for fault calculation and CRR. Chen et al., [19] proposed DFD technique with fixed range of communication to compute fault calculation and CRR. Peng Jiang [20] discussed improved DFD technique for fixed range of communication and for smaller network size to compute CRR. It is observed that the percentage CRR is 97% in the proposed algorithm compared to the less percentage CRR values in the existing algorithms. Hence the proposed algorithm is better in Correct Recognition Rate compared to existing algorithm.

TABLE III: COMPARISON OF PROPOSED WITH EXISTING ALGORITHMS

Methods	Techniques/ Architecture	Fault Calculation	Neighbour Nodes Involved	Network size	Node Involved in Fault Calculation	Range	CRR
Chiu-Ching Tuan et al ., [18]	AFTM/Automated	Averaging and comparing with allowable threshold	No	Small	Actor Node	Variable	93.9%
Chen et al ., [19]	DFD/Semi-Automated	Local comparisons are made and supported by majority voting	Yes	Small	Source Node	Fixed	83%
Peng Jiang [20]	Improved DFD/Semi-Automated	Local comparisons are made and supported by majority voting.	Yes	Small	Source Node	Fixed	94%
Ozaki et al ., [21]	FTQM/Automated	Data is sorted and then divided into four regions(Quartile)	No	Small	Actor Node	Variable	80.1%
Proposed FTNB	Proposed FTNB /Semi-Automated	Normal Bias of the neighbor nodes defines the confidence score.	Yes	large	Source Node	Fixed	97%

VI. CONCLUSION

In WSN it becomes very important to cater to sensing faults and also to distinguish between various kinds of faults and build a reliable fault tolerant strategy suitable to its class. In this paper FTNB algorithm for fault tolerance is proposed. The nodes should have at least one neighbour node so that the detected valve can be compared or be in the region of valves emitted from all the neighbour nodes. Based on the received normal the confidence score of the node is varied. This decides the correctness of the node. The proposed method has a low implementation complexity and gives better results in terms Correct Recognition Rate and False Fear Rate for varying error probabilities. In future FTNB can be integrated with communication link fault tolerance mechanism.

REFERENCE

- [1] Feng Xia.: QoS Challenges and Opportunities in Wireless Sensor/Actuator Networks.In:Journal of Sensors, ISSN 1424-8220, Vol 8, PP.1099-1110, 2008.
- [2] Lilia, Paradis, and Qi Han:A Survey of Fault Management in Wireless Sensor Networks. In: Journal of Network and Systems Management, Vol. 15, No. 2, PP.171-190, 2007.
- [3] Jonathan L. Bredin, Erik D. Demaine, Mohammad Taghi Hajiaghayi, and Daniela Rus. Deploying Sensor Networks With Guaranteed Fault Tolerance.In: IEEE/ACM Transactions on Networking, Vol. 18, No. 1, PP. 216-228, 2010.
- [4] Ing-Ray Chen, Anh Phan Speer, and Mohamed Eltoweissy: Adaptive Fault-Tolerant QoS Control Algorithms for Maximizing System Lifetime of Query-Based Wireless Sensor Networks.In: IEEE Transactions on Dependable and Secure Computing, Vol. 8, No. 2, PP. 161-176, 2011
- [5] Lifan Yuan, Yigang He, Jiaoying Huang, and Yichuang Sun: A New Neural-Network-Based Fault Diagnosis Approach for Analog Circuits by Using Kurtosis and Entropy as a Preprocessor.In: IEEE Transactions on Instrumentation and Measurement, Vol. 59, No. 3, PP. 586-595, 2010.
- [6] Hong Qiao, Jigen Peng, Zong-Ben Xu, and Bo Zhang: A Reference Model Approach to Stability Analysis of Neural Networks.In: IEEE Transactions on Systems, Man, and Cybernetics—Part B: Cybernetic.Vol. 33, No. 6, PP. 925-936, 2003.
- [7] Poornima.G, K Suresh Babu, K.B Raja, K.R Venugopal,L.M Patnaik: Fault Tolerance Using Modified Hausdroff Distance Method.In International Journal of VLSI and Embedded Systems,Vol 03,Issue 01,PP. 119-124,2012.
- [8] Mourad Elhadeif and Amiya Nayak: Comparison-Based System-Level Fault Diagnosis: A Neural Network Approach.In: IEEE Transactions on Parallel and Distributed Systems, PP. 1-14, 2011.
- [9] Kuo-Feng Ssu, Chih-Hsun Chou, Hewijin Christine Jiau, Wei-Te Hu: Detection and Diagnosis of Data Inconsistency Failures in Wireless Sensor Networks.In: Elsevier Journal of Computer Networks, Vol 50, PP. 1247-1260,2006.
- [10] Jessica Staddon, Dirk Balfanz and Glenn Durfee: Efficient Tracing of Failed Nodes in Sensor Networks.In: First ACM International Workshop on Wireless Sensor Networks and Applications, 2002.
- [11] Peng Li, Liu Kai and Liu Gang: Research on Wireless Sensor Networks Fault-tolerant Coverage Algorithm Base on Particle Swarm Optimization.In: IET International Conference on Wireless Sensor Network. Issue 15-17, PP. 286 – 290, 2011.
- [12] Duk-Jin Kim and B. Prabhakaran: Motion Fault Detection and Isolation in Body Sensor Networks.In: IEEE International Conference on Pervasive Computing and Communications, PP. 147-155, 2011.
- [13] Chessa, S. and Maestrini, P: Fault Recovery in Single-Hop Sensor Networks. In: Technical Report ISTI-2002-TR-17, Istituto di Scienze e Tecnologie dell'Informazione del CNR , PP.11, 2002.
- [14] Farinaz Koushanfar, Miodrag Potkonjak, Alberto Sangiovanni-Vincentelli: Fault Tolerance in Wireless Sensor Networks.In: IEEE Journal of Sensors, PP. 1491-1496, 2002.
- [15] Ram Rajagopal, Xuan Long Nguyen, Sinem Coleri Ergen and Pravin Varaiya: Distributed Online Simultaneous Fault Detection for Multiple Sensors.In: Proceeding of IEEE International Conference on Information Processing in Sensor Networks, PP. 133-144, 2008.
- [16] Charu Virmani and Khushboo Garg:Comparative Study of Fault Management Algorithms in Wireless Sensor Networks.In: International Journal of Engineering Research & Technology, Vol 1, Issue 3, PP.1-9, 2012.

- [17] Seo Hyun Oh, Chan O. Hong, and Yoon-Hwa Choi: A Malicious and Malfunctioning Node Detection Scheme for Wireless Sensor Networks. In: Journal of Wireless Sensor Network, Vol 4, PP.84-90, 2012.
- [18] Chiu-Ching Tuan, Yi-Chao Wu, and Wei-Shiou Chang: Fault Tolerance by Quartile Method in Wireless Sensor and Actor Network. In: IEEE International Conference on Complex, Intelligent and Software Intensive Systems, PP. 758-763, 2010.
- [19] Chen J.R, Kher, and S. Somani: A. Distributed fault detection of wireless sensor networks. In: Proceedings of the International Conference on Mobile Computing and Networking, PP. 65-72, 2006.
- [20] Peng Jiang: A New Method for Node Fault Detection in Wireless Sensor Networks. In: Journal of Sensors, Vol 9, Issue 2, PP. 1282-1294, 2009.
- [21] K. Ozaki, K. Watanabe, S. Itaya, N. Hayashibara, T. Enokido, and M. Takizawa: In: A Fault-Tolerant Model of Wireless Sensor-Actor Network. In: Proceeding of IEEE International Conference on Object and Component-Oriented Real-Time Distributed Computing, PP. 186-193, 2006.



Poornima.G received the BE degree in Electronics and Communication Engineering from Bangalore University and the M.E. degree in Digital Communication from Bangalore University, Bangalore. She is pursuing Ph.D. in Computer Science and Engineering at University Visvesvaraya College of Engineering, Bangalore

University. She is a faculty in the Dept. of Electronics and Communication Engineering, BMS College of Engineering, Bangalore. Her research interests include Computer Networks and Signal Processing. She has three research publications in refereed International Journal and Conference Proceedings. She is a life member of Indian Society for Technical Education, New Delhi.



Suresh Babu is an Associate Professor, Dept. of Electronics and Communication Engineering, University Visvesvaraya College of Engineering, Bangalore University, Bangalore. He obtained his BE and ME in Electronics and Communication Engineering from University Visvesvaraya College of

Engineering, Bangalore. He was awarded Ph.D. in Computer Science and Engineering from Bangalore University. He has over 20 research publications in refereed International Journals and Conference Proceedings. His research interests include Image Processing, Biometrics, Signal Processing, and Computer Networks.



K B Raja is an Associate Professor, Dept. of Electronics and Communication Engineering, University Visvesvaraya College of Engineering, Bangalore University, Bangalore. He obtained his BE and ME in Electronics and Communication Engineering from

University Visvesvaraya College of Engineering, Bangalore. He was awarded Ph.D. in Computer Science and Engineering from Bangalore University. He has over 60 research publications in refereed International Journals and Conference Proceedings. His research interests include Image Processing, Biometrics, VLSI Signal Processing, and Computer Networks.



K R Venugopal is currently the Principal, University Visvesvaraya College of Engineering, Bangalore University, Bangalore. He obtained his Bachelor of Engineering from University Visvesvaraya College of Engineering. He received his Masters degree in

Computer Science and Automation from Indian Institute of Science, Bangalore. He was awarded Ph.D. in Economics from Bangalore University and Ph.D. in Computer Science from Indian Institute of Technology, Madras. He has a distinguished academic career and has degrees in Electronics, Economics, Law, Business Finance, Public Relations, Communications, Industrial Relations, Computer Science and Journalism. He has authored 27 books on Computer Science and Economics, which include Petrodollar and the World Economy, C Aptitude, Mastering C, Microprocessor Programming, Mastering C++ etc. He has been serving as the Professor and Chairman, Department of Computer Science and Engineering, University Visvesvaraya College of Engineering, Bangalore University, Bangalore. During his three decades of service at UVCE he has over 250 research papers to his credit. His research interests include computer networks, parallel and distributed systems, digital signal processing and data mining.



L M Patnaik is the Vice Chancellor, Defence Institute of Advanced Technology (Deemed University), Pune, India. During the past 35 years of his service at the Indian Institute of Science, Bangalore, He has over 550 research

publications in refereed International Journals and Conference Proceedings. He is a Fellow of all the four leading Science and Engineering Academies in India; Fellow of the IEEE and the Academy of Science for the Developing World. He has received twenty national and international awards; notable among them is the IEEE Technical Achievement Award for his significant contributions to high performance computing and soft computing. His areas of research interest have been parallel and distributed computing, mobile computing, CAD for VLSI circuits, soft computing, and computational neuroscience.